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**GENERAL COGNITIVE ABILITY
PREDICTS JOB PERFORMANCE**

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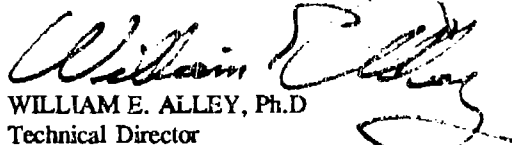
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PREFACE

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*"When a thing ceases to be a subject of controversy,
it ceases to be a subject of interest."*

William Hazlitt

SUMMARY

Many multiple aptitude test batteries, including the Armed Services Vocational Aptitude Battery (ASVAB), used for assigning or classifying individuals to jobs or for occupational counseling have subtests covering a broad range of content such as science, mathematics, reading, vocabulary, clerical, mechanical, or technical knowledge. This content reflects a belief that job performance is best predicted by subtests whose content appears to be closely related to the tasks of the job. It has been demonstrated that the subtests of a multiple aptitude test battery all measure, in large part, general learning ability in addition to the specific abilities implied by the differing contents of the subtests.

This study investigated the utility of general learning ability and specific abilities for predicting job performance criteria in eight Air Force jobs. Subjects were 1,545 Air Force enlistees. It was found that general ability was the best predictor and that specific abilities improved the predictive accuracy by a small amount. However, small increments can be useful in classification when large numbers of applicants are available to be assigned to large numbers of jobs.



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GENERAL COGNITIVE ABILITY PREDICTS JOB PERFORMANCE

I. INTRODUCTION

The concept of general cognitive ability or psychometric *g* first proposed by Galton in 1883 appeared in analyses early in this century. Spearman (1904) proposed a two factor theory of abilities including general cognitive ability, *g*, and specific abilities, *s*. The relative importance of *g* and *s* in the prediction of criteria has been and remains the center of controversy.

Early intelligence test developers such as Binet and Simon were proponents of *g* but eventually the influence of multiple ability theorists such as Thurstone (1938) was pervasive. This led to the development of multiple aptitude test batteries. The Differential Aptitude Tests (DAT), the General Aptitude Test Battery (GATB), and the Armed Services Vocational Aptitude Battery (ASVAB) were designed to measure specific abilities and to make specific predictions about employment or education. Sets of test scores would be differentially selected or differentially weighted for each situation, fulfilling a proposal by Hull (1928). It was proposed that specific abilities could compensate for a lack of general ability. The different composites of subtests used by the military for job placement or the interpretation of score profiles in counseling are current examples of the application of multiple ability theory. The use of differential weighting and different composites led to multiple aptitude theory being termed a theory of "differential validity" (Brogden, 1951).

Jensen (1980) has identified *s* with specific experience rather than with specific ability. In this same vein, Cattell (1971; 1987) posited his "investment theory" which proposes that initially there is a general ability, (called fluid *g* or *g_f*) which is invested in specific experiences and crystallizes to specific skills (called crystallized *g* or *g_c*). This means that *s* is *g* modified by experience. It implies that for an individual, the best estimate of *g* can be made from testing content in which the individual has invested their ability (*g_c*) or from tests which require little or no prior special experience (*g_f*) from training, interest, motivation, or exposure. An example of the former is that unsatisfactory estimates of *g* would be obtained by administering a French test to a sample half of which has studied French and half of which has not. The estimates of *g* for the half which did not study French would be unsatisfactory; the estimates for the other half would be more satisfactory. To rectify this problem, Raven (1938), a student of Spearman's, developed his Progressive Matrices test which measured *g* through a series of "abstract diagrammatic problems" (Vernon, 1960, p. 19) which did not require special investment of *g* but rather that *g* be used to solve nonverbal problems.

The primacy of *g* as a predictor has again become the subject of many studies. The December 1986 issue of Journal of Vocational Behavior (Gottfredson, 1986) documented the renewed interest as did the evidence emerging from validity generalization studies (Hunter, 1983, 1984a, 1984b, 1984c; Hunter, Crossen, & Friedman, 1985).

The ASVAB is an excellent source of data for investigating the value of *g* as a predictor, with over one million administrations and over 200,000 selections to job training each year.

Jones (1988) correlated the average validity of the ASVAB subtests for predicting training performance with the *g* saturation of the subtests. For each subtest, the corrected for range restricted training validities were averaged over 37 diverse Air Force technical training courses. These averages were subject weighted over a total of 24,482 technical training students. For each subtest, the *g* saturation was measured by its loading on the unrotated first principal component (see Jensen, 1987; Ree & Earles, 1991a). She found a rank-order correlation of .75, demonstrating a strong positive relationship between *g* and predictive efficiency. This was found across all jobs and comparable values were found within the four Air Force job families of Mechanical, Administrative, General Technical, and Electronics. Following Jensen (1980), the Jones rank-order correlation was calculated for the all job condition as .98 after correcting the *g* loadings for subtest unreliability.

Ree and Earles (1990) investigated the predictive utility of both the general and specific components of the ASVAB by regressing Air Force technical school grades on the unrotated principal component scores of the ASVAB. Psychometric *g* was represented by the first principal component and special or invested abilities by the remaining principal components. Across 89 jobs (individual sample sizes ranged from 274 to 3,939), the average correlation of *g* and the training criterion was .76 corrected for range restriction. When the specific (*g* x experience) components were added to the regressions, the *R* increased an average of .02.

Using a linear models approach, Ree and Earles (1991b) evaluated the nature of the relationships of *g* and specific or invested abilities to 82 Air Force job training criteria. They found statistically significant, but practically trivial, contributions (an average gain of .02) of specific or invested abilities to the regressions.

These three studies examined the predictive utility of general ability (and two the contribution of specific abilities), but none used job performance measures as criteria. Jones (1988) observed that measures of job performance were the preferred criteria but hardly ever available, frequently due to costs.

In as far as individuals sort themselves into jobs on the basis of their ability to perform, job incumbency becomes a form of job performance. Psychometric *g* as measured by the Army General Classification Test (AGCT) (Stewart, 1947) was found to be related to pre-service occupation of soldiers during World War II. Among the jobs with highest average estimated intelligence were accounting, engineering, and medicine. Jobs with middling average estimated intelligence were policeman, electrician, and meat cutter. Jobs with the lowest average estimated intelligence included laborer, farm worker, and lumberjack. The distribution of within job intelligence scores did not overlap for the very highest and very lowest jobs. This study did not consider special or invested abilities.

Hunter (1986) reviewed hundreds of studies which showed that *g* predicted job performance criteria including training success, supervisory ratings, and content valid hands-on work samples for both civilian and military jobs. However, direct tests of the incremental contribution of specific abilities for the prediction of job performance criteria were not made.

An advantage of the current study was the availability of several measures of job performance and measures of both *g* and *s*. The Air Force developed a job performance measurement system that included a work sample, an interview of job procedures, and a supervisory rating of job proficiency. The current study sought to determine if measures of *g* and *s* were differentially (Brogden, 1951) useful predictors of job performance criteria.

II. METHOD

Subjects

The subjects were 1,545 nonprior service Air Force enlistees entering from 1984 through 1988 who had tested with ASVAB parallel forms 11, 12, or 13, had completed both basic military training and technical training and were for the most part, working in their first term of enlistment. They were mostly White (78.1%), male (83.2%), 17 to 23 years old, high school or better graduates (99.1%) with an average job tenure of about 28 months.

Predictors

The Armed Services Vocational Aptitude Battery is a multiple aptitude test battery (DOD, 1984) composed of ten subtests as shown in Table 1. Except for the Numerical Operations

and Coding Speed subtests which are speeded, all are power tests. It is used for enlistment qualification and initial job assignment. The battery was normed on a sample of 18-to 23-year-old youths weighted to be nationally representative (Maier & Sims, 1986; Ree & Wegner, 1990). The ASVAB has been used in this subtest configuration since 1980. Its reliability has been studied (Palmer, Hartke, Ree, Welsh, & Valentine, 1988), and it has been validated for many military occupations (Earles & Ree, in press; Welsh, Kucinkas, & Curran, 1990; Welsh, Trent, Nakasone, Fairbank, Kucinkas, & Sawin, 1990; Wilbourn, Valentine, & Ree, 1984).

The Air Force aggregates the subtests into four composites in a reified belief in differential validity. These composites are Mechanical ($M = MC + GS + 2AS$), Administrative ($A = NO + CS + WK + PC$), General-Technical ($G = WJ + PC + AR$), and Electronics ($E = AR + MK + EI + GS$).

Table 1. Subtests of the ASVAB

<u>Subtests</u>	<u>Number of Items</u>	<u>Time in Minutes</u>	<u>Reliability</u>
General Science (GS)	25	11	.80
Arithmetic Reasoning (AR)	30	36	.87
Word Knowledge (WK)	35	11	.88
Paragraph Comprehension (PC)	15	13	.67
Numerical Operations (NO)	50	3	.72
Coding Speed (CS)	84	7	.77
Auto and Shop Information (AS)	25	11	.82
Mathematics Knowledge (MK)	25	24	.84
Mechanical Comprehension (MC)	25	19	.77
Electronics Information (EI)	20	9	.71

Note. Test-retest reliability estimates taken from Palmer et al. (1988).

There are three generally accepted ways of estimating the g component of a set of variables (Jensen, 1980). Ree and Earles (1991) have shown that for the ASVAB, estimates of g from these three methods, principal components, principal factors, and hierarchical factor analysis, all correlated greater than .996. Because of high correlations among the various g estimates and the mathematical simplicity of the principal components, they were chosen to represent the general, g, and specific (or invested), s, measures of the ASVAB. The first unrotated principal component serves as a measure of g (Jensen, 1980). Specific abilities are often represented by group factors from common factors analyses with g ineluctably distributed through them from rotation (Jensen, 1980). The g can be removed from the lower order factors through the Schmidt-Leiman (1955) procedure. However, common factors procedures do not account for all the variance in the variables and put the specific variances at a relative disadvantage compared to principal components procedures which do account for all the variance and provide maximum advantage for the specific abilities.

To determine the maximal predictive efficiency (Brogden, 1946) of the specific abilities, the best choice is the procedure which most fully represents the non-g portions. Therefore, the nine remaining unrotated principal components were used as the measures of specific or invested abilities (s_1 to s_9). These are mathematically defined measures of specific abilities and do not necessarily represent identifiable or namable concepts. Jones (1988) investigated the second principal component and found it to be gender related. When a variable for gender was included in the principal component analysis, it loaded highest on the second component by a considerable amount. If the investment theory holds this principal component which positively weights the two subtests which female means exceed male means and negatively weight subtests where male means exceed female means is an expression of differential investment.

The principal components have the additional benefit of being orthogonal (Hotelling, 1933a, 1933b) which, according to Kendall Stuart and Ord (1983), avoids the problems of colinearity and enhances their usefulness in regression.

Tables 2 and 3 present the principal component score weights and principal component loadings.

Table 2. Principal Component Weights for the ASVAB Subtests

	Principal Components				
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>
GS	.13808	-.11244	-.21982	-.29416	.19523
AR	.13715	.03854	-.39912	.54694	-.02066
WK	.13736	.06649	-.21381	-.64261	-.08976
PC	.12778	.16656	-.31273	-.71570	-.02359
NO	.11291	.38342	.42663	.23843	-1.36760
CS	.09956	.44464	.75816	.03679	1.11560
AS	.10878	-.43374	.60474	-.00918	-.34001
MK	.12965	.12086	-.61486	.64452	.20353
MC	.12448	-.30623	.21087	.39938	.36281
EI	.12857	-.29635	.14351	-.13640	-.00001
	<u>6</u>	<u>7</u>	<u>8</u>	<u>9</u>	<u>10</u>
GS	-.88893	-1.05107	.56764	.46367	-1.25618
AR	.26159	.58641	.25640	-1.51740	-1.06178
WK	-.20343	-.35471	.19392	-1.22910	1.53259
PC	1.10958	.48914	-.18581	.83254	-.55741
NO	-.11449	-.39672	-.29306	.20266	-.11527
CS	-.14894	.21734	.13184	-.06193	-.04099
AS	.22086	.62982	1.28388	.27471	.26269
MK	-.26607	.28551	.29615	1.16925	1.09690
MC	.89768	-1.19071	-.72807	-.02996	.28081
EI	-.78167	.90823	-1.43032	.09391	-.06884

Note. Weights computed in the ASVAB normative sample. See Ree and Earles (1990).

Table 3. Unrotated Principal Components Loadings for ASVAB Subtests

	Principal Component									
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>	<u>7</u>	<u>8</u>	<u>9</u>	<u>10</u>
GS	.88	-.14	-.11	-.14	.05	-.24	-.22	.11	.07	-.18
AR	.87	.04	-.20	.27	.00	.07	.12	.05	-.24	-.15
WK	.87	.08	-.11	-.32	-.02	-.05	-.07	.03	-.19	.22
PC	.81	.21	-.16	-.36	.00	.29	.10	-.03	.13	-.08
NO	.72	.49	.22	.12	-.39	-.03	-.08	-.06	.03	-.01
CS	.63	.57	.39	.01	.32	-.04	.04	.02	.00	.00
AS	.69	-.55	.31	.00	-.09	.05	.13	.26	.04	.03
MK	.82	.15	-.32	.32	.05	-.07	.06	.06	.18	.16
MC	.79	-.39	.11	.20	.10	.24	-.25	-.14	.00	.04
EI	.82	-.38	.07	-.06	.00	-.21	.19	-.29	.01	-.01

Note. Loadings computed in the ASVAB normative sample. See Ree and Earles (1990).

Jobs

Eight jobs were selected to be representative of all Air Force jobs. Each job had a minimum requirement on one of the four composites. Jet Engine Mechanic and Aerospace Ground Equipment Specialist were selected by the M composite; Information Systems Operator and Personnel Specialist by the A composite; Air Traffic Controller and Aircrew Life Support specialist by the G composite; and Precision Measurement Equipment Specialist and Avionics Communications Specialist by the E composite.

Criteria

The criteria were developed as part of the Joint-Services Job Performance Measurement Project (Wigdor & Green, 1987). The measures used in the present study were hands-on-work samples (HOPT), technical interviews (INT) in which the subjects explained how to perform technical tasks, and the combination of HOPT and INT called a Walk Through Performance Test (WTPT) (Hegde & Lipscomb, 1987). A secondary or surrogate measure was task ratings by supervisors (SUPR). Because the WTPT was expensive to develop and administer the surrogate was included in an effort to obtain measures of job proficiency at a lower cost.

Work sample criterion development. A hands-on work sample test (HOPT) was constructed for each job to assess proficiency on representative job tasks. The task domains for each job were identified and defined from the Air Force Occupational Survey data base (Christal, 1974). A domain sampling plan was developed (Lipscomb, 1984), and tasks were sampled with stratified random sampling procedures (Lipscomb, 1984; Lipscomb & Dickinson, 1988).

For each task, work sample developers used technical descriptions of work procedures (Air Force technical orders and manuals) as well as input from subject matter experts (SMEs) to define and describe the procedural steps required for successful task completion. A hands-on work sample test was constructed for each task, reviewed by SMEs, and field tested at several Air Force bases. A "yes/no" format was used to rate the performance on each procedural step within the task. The proportion of steps performed correctly was calculated for each task and this value was the score. Each job had multiple tasks.

Work sample administrator training. The work sample tests were administered to the subjects and rated by active duty or retired noncommissioned officers with extensive job experience. The raters received one to two weeks of scorer accuracy training and observation (Hedge, Lipscomb, & Teachout, 1988). Videotapes of work sample test performance with known target ratings were used as training devices. After viewing and rating the videotapes, the administrators discussed the key work behaviors to perform or avoid for successful task completion. Hedge, Dickinson, and Bierstedt (1988) reported that this training produced accurate and reliable work sample test rating. The raters demonstrated high average agreement ($r = .81$) and high average correlational accuracy ($r = .85$) between their ratings and videotape target ratings.

In addition, a "shadow scoring" technique was used during a portion of data collection with 58 subjects which required two test administrators to observe and rate task performance. The technique was effective in maintaining agreement in the scoring of the work sample tests. The average scorer-shadow scorer agreement was 95% across the 58 subjects.

Supervisory ratings. Graphic rating scales were developed to measure technical proficiency on the same tasks measured by the Walk Through Performance Test. Each task was described by its statement from the Air Force Occupational Survey. Task performance was rated on a 5-point adjectivally anchored scale.

Supervisory ratings training. In a group rater orientation session, the project was described, participation conditions explained, and rating measures presented. This orientation was followed by one hour of frame-of-reference and rater error training (McIntyre, Smith, & Hassett, 1984). Two rating exercises facilitated use of rating forms by identifying varying levels of performance and their associated rating-scale anchors. Participants practiced rating the performance of incumbents described in the two exercises. Following these ratings, they received target-score accuracy feedback. In addition, a third exercise highlighted rating errors, and how to improve rating accuracy.

Procedures

Data collection. Criterion data were collected as part of a project to validate selection and classification tests (Hedge & Teachout, 1986). Immediately following rater training, rating booklets were distributed, and the supervisors completed the rating forms. Subsequent to the group session, job incumbent subjects were individually administered the WTPTs. Time limits were specified for each WTPT, ranging from four to seven hours.

Analyses. Each criterion was regressed against the set of principal components for each job in a forward stepwise manner with no order of inclusion specified. This was accomplished for the correlations artifactually depressed by prior selection. To make better estimates of the correlations in the unrestricted population, the regressions were also computed in matrices after multivariate correction for range restriction. The Type I error rate was set at $p < .01$.

The F-test statistic for regression (stepwise and non-stepwise) uses the error sum of squares in computation (Ward & Jennings, 1973). The equation below compares two linear models such as is done to determine if another variable can be added in stepwise regressions or when a regression is tested to determine if it is significantly different from zero. There is an algebraically equivalent variant of this equation using R^2 's, but the ratio remains the same and the F value remains the same.

$$F = ((ESS_1 - ESS_2) / (df_1 - df_2)) / (ESS_2 / df_2)$$

Where ESS_1 is the error sum of squares for the restricted model and ESS_2 is the error sums of squares for the full model and these are divided by their respective degrees of freedom.

One of the assumptions of the correction for range restriction is that the variance error of estimate (alternate name for the error sum of squares divided by degrees of freedom) are equal in the uncorrected and the corrected regression. The error sum of squares does not change from application of the correction. The computation of the F in the restricted sample and in the corrected sample is therefore algebraically equivalent. This allows for the computation of the F test for significance of a difference of regressions between two models in the corrected matrices.

III. RESULTS AND DISCUSSION

These analyses disclosed that the principal components were useful in predicting the criteria, as found for training criteria (Ree & Earles, 1990; Ree & Earles, 1991b). The specific or invested abilities, as represented by the second through tenth principal components, added to the accuracy of prediction, but by a small amount. The efficiency of the predictors (uncorrected correlations; r and R) in this study were smaller than in a previous study (Ree & Earles, 1990). The sample sizes in this study were much smaller so that some portion of the increases due to specific or invested ability are likely to be the results of overfitting and likely

to diminish on cross-validation. These regression results are reported in Table 4. The correlations within parentheses are estimates of cross-validation coefficients by use of Stein's expectancy operator (see Kennedy, 1988).

Table 4. Correlations and Regressions of Measures of g and s With the Criteria

AFSC 122X0 (n = 162) Aircrew Life Support Specialist					
<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>
	r_g	r_s^c	R_{g+s}	R_{g+s}^c	Uncorrected Corrected
HOPT		No significant correlations.			
INT			-.28*	-.26	2 2
			(-.24	-.22)	
WTPT		No significant correlations.			
SUPR		.24			1
		(.19)			

AFSC 272X0 (n = 164) Air Traffic Control Operator					
<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>
	r_g	r_s^c	R_{g+s}	R_{g+s}^c	Uncorrected Corrected
HOPT		No significant correlations.			
INT		.25		.33	1, 5
		(.21)		(.28)	
WTPT		.26			1
		(.22)			
SUPR		.23			1
		(.18)			

Table 4. (Cont'd)

AFSC 324X0 (n = 126) Precision Measuring Equipment Specialist

<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>	
	r_g	r_g^c	R_{g++}	R_{g++}^c	Uncorrected	Corrected
HOPT	.34 (.30)	.69 .68	.45 .41	.76 .74)	1,4	1,4
INT	.32 (.28)	.75 .74)			1	1
WTPT	.36 (.32)	.71 .70	.45 .41	.77 .75)	1,4	1,4
SUPR	No significant correlations.					

AFSC 328X0 (n = 74) Avionics Communications Specialist

<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>	
	r_g	r_g^c	R_{g++}	R_{g++}^c	Uncorrected	Corrected
HOPT	.34 (.27)	.72 .71	.72	.75 .72)	1	1,8
INT	.26 (.16)	.61 .58	.41 .32	.73 .69)	8,1	1,8,3
WTPT	.34 (.27)	.71 .69	.55 .48	.81 .78)	1,3,8	1,8,3
SUPR		.36 (.30)		.55 (.48)		1,6,8

Table 4. (Cont'd)

AFSC 423X5 (n = 211) Aerospace Ground Equipment Specialist

<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>	
	r_g	r_g^c	R_{g+u}	R_{g+u}^c	Uncorrected	Corrected
HOPT	.29 (.26)	.42 .40	.41 .37	.57 (.54)	5,1,2	1,2,5
INT	.19 (.14)	.31 .28	.28 .23	.45 (.41)	2,1	1,2,5
WTPT	.26 (.23)	.38 .36	.39 .35	.53 (.50)	5,1,2	1,2,5
SUPR	No significant correlations.					

AFSC 426X2 (n = 178) Jet Engine Mechanic Specialist

<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>	
	r_g	r_g^c	R_{g+u}	R_{g+u}^c	Uncorrected	Corrected
HOPT		.25 (.21)		.31 (.26)		1,5
INT	.25 (.21)	.43 .41		.47 (.44)	1	1,2
WTPT	.19 (.14)	.35 .32			1	1
SUPR				.20 (.15)		4

Table 4. (Cont'd)

AFSC 492X1 (n = 111) Informations Systems Radio Operator

<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>	
	r_g	r_g^c	R_{g+}	R_{g+}^c	Uncorrected	Corrected
HOPT		.28 (.22	-.30 -.21	.40 (.34)	3	3,1
INT	.32 (.27	.32 (.27)		.40 (.34)	1	1,3
WTPT	.27 (.21	.34 (.30	.37 (.31	.44 (.39)	1,3	1,3
SUPR	.28 (.22	.50 (.47)			1	1

AFSC 732X0 (n = 172) Personnel Administration Specialist

<u>Criteria</u>					<u>Order of Entry of Principal Components in Equation</u>	
	r_g	r_g^c	R_{g+}	R_{g+}^c	Uncorrected	Corrected
HOPT	.22 (.17	.49 (.47)			1	1
INT		.46 (.44)		.50 (.47)		1,2
WTPT	.21 (.16	.53 (.51)		.56 (.54)	1	1,2
SUPR	No significant correlations.					

Note. Correlations with superscripts c indicate correction for range restriction. Correlations without superscripts are as observed. Correlations within parentheses are cross-validation estimates using Stein's expectancy operator. r_g is the correlation of g and the criterion, r_g^c is the correlation between g and the criterion corrected for range restriction, R_{g+} is the multiple correlation between several principal components and the criterion and R_{g+}^c is the corrected for range restriction multiple correlation.

The stepwise regressions in the corrected matrices, the superior parameter estimates, revealed a situation much closer to previous findings. Psychometric g entered 24 times out of 32 regression analyses of four criteria on eight jobs. Twenty-three times g entered first. The reason for the disparity between these findings and the findings in the uncorrected (incorrect) correlations are the artifactual nature of observed correlations (Hunter, Schmidt, & Jackson, 1982). Stepwise regression methods begin by determining the highest correlation among the predictors with the criterion. When the highest correlation is different in the selected sample than in the population, the order of regression will change. Just as artifacts cloud the interpretation of observed correlations, unless subjected to proper estimation correction techniques, so too the observed uncorrected correlations reported here are liable to misinterpretation.

Hands-on-work samples. Using HOPT as the criterion and computing stepwise regressions using the uncorrected correlations, five of the eight jobs showed significant prediction by ability. In these regressions, g was the predictor to enter first three times and specific abilities added only to two of these three. Psychometric g entered the regression equation in 2nd order for one job.

Without corrections for artifactual depression, the average correlation of g and the HOPT criterion was .30 for the four jobs. In the two instances where s added to g the average increment was .12. Across all four jobs, the average increment to g was .06.

When HOPT was regressed against the predictors using the correlation matrix corrected for restriction of range, six of eight jobs showed correlations of ability and HOPT. In five of the six regressions, g entered first with an average simple correlation of .51. In four AFSCs with the data fully corrected, s added an average .08 to the prediction. For all six jobs where aptitude predicted job performance e.g., including the two where s added nothing, the average addition dropped to .05.

One job, Information Systems Radio Operator, showed a significant prediction of HOPT by the third principal component ($r = -.30$) in the uncorrected data. In the corrected data principal component three enters first ($r = -.29$) and g increases the prediction ($R = .40$). Psychometric g was the best predictor for HOPT.

Interview Testing. When INT was the criterion in the uncorrected regressions, g entered the stepwise procedure first three times in six jobs when aptitude predicted job performance. The average correlation of g in these three was .30. Specific or invested abilities added nothing in these three cases.

In three jobs, specific or invested abilities entered the regressions first. These were not the same ss in each case. On average the correlation of specific ability and job performance was .32.

In corrected regressions, there was significant prediction of the criterion and g entered first

for each job with an average correlation of .45. Measures of specific or invested abilities added six times (out of seven) with an average increment of .08.

Principal component two was the only significant predictor of INT for the job of Air Crew Life Support Specialist in the uncorrected and corrected analyses. The correlations were -.28 and -.26, respectively. Psychometric g was the best predictor of the technical interviews.

Walk Through Performance Test. The WTPT is a combination of the HOPT and the INT and provides better content sampling of the tasks in the jobs. When stepwise regressions were computed in the uncorrected data, g entered in six jobs (five times in first order; average $r = .27$) when there was prediction of the criterion. The average correlation of g and the criteria was .27 in all jobs where significant prediction occurred and s added to g in four jobs for an average increase in predictive efficiency of .13 on those four jobs and .02 when all six significantly predicted jobs were included in the average.

Computing the regressions in the fully corrected data there was significant prediction for seven of the eight jobs and g entered first in all seven for an average correlation of .47. Specific or invested abilities improved prediction in five jobs with an average increase of .09. The average gain for the seven jobs was .06. As before, psychometric g was the best predictor of WTPT.

The job performance WTPT criterion for Aircrew Life Support Specialist was not predictable by aptitude.

Supervisory Task Ratings. Analyses of SUPR were conducted in the same way as the other criteria. There was significant prediction of the criteria in the uncorrected data for only one job, Information Systems Radio Operator. The correlation, .28, was due to g. The measures of s did not add to the regression.

In the corrected analyses, five jobs were significantly predicted and in four of these g entered and in each case, first. In the fifth job, Jet Engine Mechanic, only the fourth principal component was a significant predictor. The average correlation of g for the four jobs was .34 and for one job, Avionics Communications Specialist, s added an increment of .19 to the prediction afforded by g.

In three jobs, the criterion of SUPR could not be predicted. These were Precision Measuring Equipment Specialist, Aerospace Ground Equipment Specialist, and Personnel Administration Specialist.

The corrected analyses provided the best estimates of the correlations in the population. They therefore present the best expressions of the relationships between the criteria and the predictors. There were 32 regressions calculated (8 jobs x 4 criteria = 32) and in 26 of these, significant prediction occurred. In these 26, g entered stepwise regressions first 23 (88%) times (See Table 5). In two of the remaining three cases, g was not predictive.

Sixteen times in the 23 regressions where g entered first other principal components added to the regression. The average corrected-for-cross-validation (Kennedy, 1988) increase in R due to s adding to g when g entered first was .06.

Table 5. Count of Principal Components Entering Regression Equations by Criterion Measure

Frequency of Entry of Principal Components										
Criterion	Component									
	1	2	3	4	5	6	7	8	9	10
HOPT	6	2	1	1	2	0	0	1	0	0
INT	7	4	2	0	2	0	0	1	0	0
WTPT	7	2	2	1	1	0	0	1	0	0
SUPR	5	0	0	2	0	1	0	1	0	0

Note. The first principal component is g. Frequencies are based on regressions using correlation matrixes corrected for restriction of range.

In all 24 instances where g significantly entered the regression, regardless of order, the average correlational increase using g plus s was .06 corrected for cross-validation by Stein's operator (Kennedy, 1988).

Except for g, interpretation of the principal components which entered the regressions was difficult. In general, there was little similarity of which principal components were predictive for which jobs. For example, the two jobs which the Air Force uses G to select had different components potent in prediction. For the two E jobs, the only common principal component was g. Principal component 4 added to the prediction afforded by g for one job and principal components 3, 6, and 8 for the other. Much the same was found for the A jobs with g the common predictor and principal component 3 adding to prediction in one job and principal component 2 in another.

The two M jobs had similar patterns of prediction by the principal components. In both cases, principal components 2 and 5 increased prediction beyond g. Principal component 2 is reasonably a surrogate for gender (Jones, 1988) with its negative weighting on technical subtests and its positive weighting on speeded subtests. It separates those who perform well in subtests such as Auto & Shop Information (males) and Electronics Information (males) from those who perform well in the two speeded subtests (females). Principal component 5

was less interpretable but separated those who did well in one speeded subtest, simple arithmetic--Numerical Operation, from those who did well in the other speeded subtest, selecting from a table the number associated with a word--Coding Speed.

In previous studies (Ree & Earles, 1990; 1991b) when the principal components were used to predict training grades, it was found that g was the most potent predictor and that the specific or invested abilities added little to prediction. The same was true for predicting the job performance criteria but not as strongly as for training criteria.

For these job performance criteria, the potential exists that specific or invested abilities will offer classification utility. Studies to illuminate the theoretical and practical consequences of optimum classification such as sex bias, ethnic bias, adverse impact, regression effects, within job ability distributions, and individual vocational interest need to be accomplished.

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